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Disaster Relief Models: Location of Points of Distribution

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Disaster Relief Models : Location Of Points Of Distribution

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Abstract

This project consists of developing a Location Allocation model that focuses on determining the locations of relief supply Points of Distribution (PODs) after a natural disaster and how to assign demand points to them. According to FEMA, PODs are “centralized locations where the public picks up life sustaining commodities following a disaster or emergency” [1]. After each disaster, decisions have to be made to ensure a good delivery of resources in a timely manner. The road infrastructure may be damaged due to the disaster. Some roads might become inoperable, and some bridges are expected to fail. The model studied in this research makes decisions about the locations of PODs after knowing the real-time information about the road infrastructure and magnitude of demand at the beginning of each period of the planning horizon.

A case study developed based on the New Madrid Seismic Zone (NMSZ) is used to demonstrate the usefulness of our model. Our study area is limited to the nineteen counties in Arkansas that are most likely to be affected by the New Madrid earthquake. Many lives can be saved if a good logistics plan exists. A good humanitarian logistics plan can reduce the suffering of the affected population and the cost associated with providing supplies. This project extends previous work completed as part of the Department of Transportation Mack Blackwell Transportation Center Project 3028, “Models for Disaster Relief Shelter Location and Supply Routing” [2]. We examine 96 potential disaster scenarios by alternating problem parameters. We are considering four road networks instances, three budgets, four demand patterns, and two POD capacities. An offline model is used in order to compare the online model results.

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1. Background/ Motivating Case Study

In 1811-1812, The New Madrid Seismic Zone experienced a series of magnitude eight earthquakes. If such a scenario occurred today, the damage would be devastating. Logistical decisions, about where to locate the Points of Distribution (PODs) and which demand points to assign to them, have to be made.

In case of a 7.7 magnitude earthquake in the New Madrid Seismic Zone, eight states are expected to be affected: Alabama, Arkansas, Indiana, Kentucky, Mississippi, Missouri, Ohio, and Tennessee. Over 3,600 bridges are expected to be damaged. By day three, over 7.2 million people will be in need of support, with over 2,000,000 population seeking shelter. More than 1,280 water trucks, 705 Meals Ready to Eat (MREs) trucks, and 1,533 ice trucks are needed to support the affected population. In Arkansas alone, 169 truckloads of water and 93 truckloads of meals are expected to be needed [3].

It is impossible to predict an earthquake's magnitude and time of occurrence, and the location and magnitude of demand. These factors make planning complicated and almost impossible. The model created in this research makes decisions about where to locate PODs and which demand points to assign to them. This type of model is known as a location/allocation model. Two types of models have been created. The online approach model relies on real time information in order to make decisions, which means that the information associated with the road network, demand location and magnitude are revealed in an ongoing fashion after the earthquake occurs. The offline model is used for comparison with the results of the online approach model. The offline model assumes that all information is known in advance. At the time of the disaster, offline solutions are not an option, since it is impossible to know all information at time zero. The offline solutions serve as a reference to how good the solutions could be if all information were available as soon as the disaster occurred. The availability of information is the main difference between the online and offline approaches, so, for our case study, even a good online solution will serve less demand than the offline solution. The model consists of determining the POD locations to open and when to open them in order to maximize population access to supplies, taking into consideration the budget constraint and road limitations.

A good logistics plan will help maximize the population served while minimizing social costs such as travel time for the affected population. However, due to the infrastructure constraints, it may be that not all the population can be served.

2. Literature Review

Previous research has studied the problem of locating Points of Distribution following a disaster. However, the existing literature focuses mostly on the pre-disaster phase. Disaster operations can be divided in two main stages: pre-disaster and post disaster. The pre-disaster stage consists of the mitigation and preparedness phases. While the mitigation phase consists of preventing the disaster or reducing its impact, the preparedness phase consists of making response plans. The post disaster consists of response and recovery phases. The response phase starts immediately after the disaster and consists of activities that reduce the impact of the disaster on the affected population. The mitigation phase focuses on the long term activities that will lead to restoring the impacted region [4].

The previous research efforts differ from each other based on the objective considered and the information that is not assumed to be known with certainty. Some studies use non-traditional objective functions to capture the costs associated with opening PODs. A study by Yushimoto et al. (2012) aims to determine where to locate Distribution Centers (DCs) in order to maximize the coverage of the affected regions while minimizing a function of urgency that depends on distance [5]**.** It is assumed that travel time and demand is known with certainty. On the other hand, Balcik and Beamon (2008) developed a model that is only concerned with maximizing the service to the affected population [9]. The model solves the problem of determining the location and number of PODs to open, and the amount of supplies to assign to each one. Campbell and Jones (2011) used a cost model in order to determine where to preposition supplies and the quantity that should be stored [6]. The model consists of choosing the best point of distribution location from a finite number of choices based on combinations of distance and the uncertainty associated with failure. Pre-positioning supplies close to the expected disaster location will reduce the distance, thus the cost associated with transportation; however, it will increase the probability of failure [6]. Rawls and Turnquist (2010) developed a stochastic model that aims to determine where to preposition supplies and the quantity of supplies given that there is uncertainty associated with demand locations, demand magnitude, and transportation network status. The objective function is to minimize the total cost associated with the decision. The total cost is a function of resource purchase costs, opening facility cost, and transportation costs [7]. Jaller and Holguin-Veras (2011) developed a model that estimates the needed number of points of distribution and their capacity in case of a disaster. The model aims to reduce the total cost. The total cost was modeled as a function of monetary cost and social cost. The monetary cost is represented by the fixed costs associated with opening a facility, while the social cost is represented by the waiting time of individuals, and traveling time [8].

De la Torre et al.'s (2012) research presents a comprehensive summary of different researches concerning disaster relief routing. They describe the objective of each model and its unique characteristics [12]. Since our problem is more a location/allocation problem, this research is not discussed in detail in this paper. The problem we are solving is different from those we have reviewed because it focuses more in the post disaster phase rather than the pre-disaster phase. The model determines which PODs to operate and thus how many to operate, given that the demand and the infrastructure is revealed on an online fashion taking in consideration budgetary, capacity, and other logistical constraints.

3. Problem statement and formulation

After the occurrence of a disaster, demand for commodities such as food and water arises from a set of demand points I with known locations and magnitudes. On the other hand, a set of possible PODs J locations is known with their associated capacities. At the beginning of each period t of the planning horizon with length T, a cost h_{ijt} is associated with moving from the demand points to the POD locations. The cost represents the shortest distance between demand point i and POD location j. Due to the road infrastructure damage, not all of the demand points i and PODs j are connected. Moreover, the shortest path at period t might be different than the pre-disaster shortest path. The main objective for this problem is to maximize the total demand served during the entire planning horizon. A secondary objective is introduced that aims to reduce the total distance traveled between the demand points and the PODs without affecting the POD location decisions. A total budget B is available to open and operate the PODs. There is a one-time cost C_f associated with opening the POD for the first time, and a variable cost C_o associated with operating the POD each period. The decisions to be made are as follows:

- Which PODs to open?
- What demand points to assign to each open POD?
- What portion A_{ijt} of demand associated with the assigned demand points to serve?

However, some logistical constraints have to be met:

- If POD *j* is open at period *t*, it must stay open for the remaining time periods.
- A demand point *i* can only be assigned to a single POD *j*.
- A demand point *i* can only be assigned to a POD *j* within the maximum allowable distance *D* (25 miles for the purpose of our problem).
- If a portion of demand A_{ijt} is served at period *t*, at least the same portion of demand has to be served at period *t+1*.
- If a demand point *i* is served by POD *j* at period *t*, it must be served by the same POD *j* for the remaining of the planning horizon.

The mathematical models used are provided in Appendix A. They were directly retrieved from [2].

4. Case Study Development

In order to be able to realistically create a scenario similar to a potential NMSZ earthquake, it was necessary to determine a planning horizon, possible candidate locations for PODs, and demand points [2]. ArcGIS was used to determine the road network and the connectivity between the PODs and demand points.

4.1 Planning Horizon

The PODs typically operate only for a few days after a disaster. Their operation lifetime is between three to seven days, as demand begins to decrease after the seventh day [13]. This is likely due to the impacted populations relocating to unaffected areas and becoming more self-sustaining. For the purpose of this project, the planning horizon is seven days [2]. The beginning of each day is considered the beginning of planning period *t* (1, 2, 3…7).

4.2 Points of Distribution

After the occurrence of a disaster, the sustaining commodities are moved to large centralized locations that resisted the earthquake. Schools are considered good candidates for PODs as they are generally large and in the center of population. A list of schools in the impacted area is gathered from the EducationBug website [14]. According to the POD guide published by FEMA, there are three types of PODs:

- Type I (Small capacity) POD: can service up to 5000 people per day.
- Type II (Medium Capacity) POD: can service up to 10000 people per day.
- Type III (High capacity) POD: can service up to 20000 people per day [1].

We chose to consider medium capacity and high capacity PODs due to the demographics of the impacted counties. It was assumed that the fixed cost associated with opening the two types of PODs is the same; however, the variable cost associated with operating the facility is twice as much for the high capacity PODs. For the purpose of our case study, we assumed that it takes one unit cost to open medium and high capacity PODs for the first time, while it takes one unit of cost to operate medium capacity and two units of cost to operate high capacity PODs for every day of the planning horizon.

4.3 Demand Points

The NMSZ earthquake is expected to affect nineteen counties, leaving almost 480,000 without water and/or power, and 150,000 shelter seeking population by day three after the earthquake [3].

The origination point of demand was obtained by dividing each county into subdivisions based on a census report [15]. Since a demand point with a demand magnitude greater than 10,000 cannot be fully served by a single medium capacity POD, four of the subdivisions that had more than 10,000 population demand at a certain day were divided into n sub-regions such that each region have a maximum of 10,000 demand magnitude while keeping n at its minimum. We obtained a total of 343 possible demand points.

4.4 Demand Magnitude

In the previous research by Milburn et al. [2], the NMSZ Catastrophic Event Planning report was used to provide estimates of the percentage of the expected shelter seeking population in each of the affected counties on day one and three. The affected population percentage for days five through seven was developed based on the demand pattern of hurricane Katrina [16]. However, for the purpose of this thesis, we conduct sensitivity analysis on this parameter by using four demand patterns. We used a decreasing, increasing, constant, and expected demand pattern [2]. The decreasing demand pattern assumes that demand starts high during the first two days and then starts decreasing for the rest of the planning horizon. The increasing demand pattern assumes that demand starts low and then starts increasing until it reaches its maximum on day six and seven. With a constant demand pattern, the demand magnitude of each demand point is assumed to be constant throughout the planning horizon. The total demand associated with each of the demand patterns throughout the planning horizon is the same for the four demand patterns. While one of the four demand patterns represents an expected pattern, the other three (constant, increasing, decreasing) represent extreme cases of demand patterns. Tables 32,33,34,35 on appendix C summarize the percent demand by county for each day for the four different demand patterns. For the four different instances, the total demand over the planning horizon is the same so that we can compare the results.

4.5 Road Network

ArcGIS, a software from ESRI, is used to model the underlying road network. “StreetMap North America – Detailed Streets” is used as the road network in the study region. The inoperable transportation infrastructure after an earthquake is modeled as barriers in ArcGIS. The probability of having a bridge fail from the NSMZ report is used to determine a list of bridges failing during each day of the planning period. Having a road barrier affects the shortest distance between the demand points and the PODs. Figure 1 describes how barriers affect the shortest path between PODs and demand points [2].

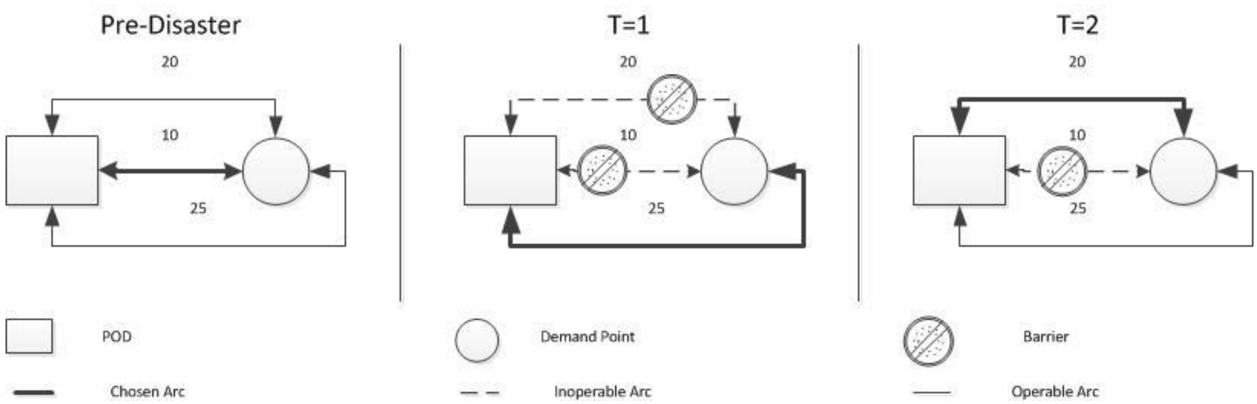

Figure 1: Effect of failed bridges on shortest paths between a demand point and POD

Before the occurrence of the earthquake, the shortest road between the demand point and POD is the middle road. At time period one (t=1), the middle road and top road become inoperable, making the bottom path the shortest operable road between POD and demand point with a cost of 25. In time period two (t=2), the top road is operable again, which makes it the shortest path with a cost of 20 [2]. For more details about the case study development refer to [2]. Four road instances were developed. The only difference between the four instances is the barriers disrupting the network, which changes the shortest distances and the connectivity between the demand points and PODs.

4.6 Budget

We decided to use three different levels of budget 368 (high budget), 184 (medium budget), and 92 (low budget). A high budget is considered as the best case scenario. With a high budget, it is possible to open and operate 46 PODs from day one. Theoretically, opening 46 PODs should be enough to satisfy all the demand throughout the planning horizon. A medium budget is enough to open enough PODs for the first time at day five, in which demand reaches its maximum using an expected demand pattern, and services the whole demand during the remaining planning horizon. A low budget was used in order to determine the decisions made with extremely low budgets.

5. Results Discussion

The differences between the online and offline models can be seen in Table 1.

Table 1: Characteristics of the online vs. offline models

Characteristics	Online model	Offline model
Distance between Demand point *i* and POD *j* at time t	Known at the beginning of period *t*	Known at time zero
Demand magnitude	Known at the beginning of period *t*	Known at time zero
POD candidates	Known at time zero	Known at time zero

Since all the information of the offline problem is known in advance, it will lead to a better solution than the online approach. The online model has to make a decision to open a POD or not without knowing the future demand magnitude and road network. It is hard to decide to either open a POD at time *t* and serve the demand and commit to serve it in future periods, versus waiting until a future period and saving the one-time and variable costs until that future period .

This section focuses on the discussion of the results of the 96 offline instances solved using CPLEX[1], and the online solution solved using the algorithm described in Appendix A**.** Our analysis considers the effect of varying:

[1]All experiments were performed using CPLEX 12 on a DELL computer with an Intel® Core™ i7 CPU 2.93 GHz processor and 8 GB of RAM

- Budget: three different budgets
- Demand Pattern: expected, increasing, decreasing, constant
- Types of PODs: medium capacity and high capacity
- Road networks: four different road network instances

We accounted for 343 possible demand points, and 127 candidate locations for PODs. The cost associated with opening a POD for both medium capacity and high capacity is one, while the cost associated with operating a medium capacity and high capacity POD is one and two respectively. The four road networks are different; however, they have the same magnitude of inoperable roads due to the random selection of the barriers.

In each road network instance, there were some demand points that were not connected to any of the demand points either throughout the whole planning horizon or just for certain periods. For the purpose of this project, we consider a demand point not connected if it is not connected or not within the minimum allowable distance *D* to a POD (25 miles). Table 2 summarizes the number of connected demand points for each of the instances per day:

Table 2 : Number of connected demand points per day

	Day 1,2	Day 3,4	Day 5,6,7
Instance 1	325	328	328
Instance 2	328	333	333
Instance 3	329	329	331
Instance 4	324	327	328

The total demand over the planning horizon is the same; however, since we are using 4 different demand patterns, the demand for each day is different. Figure 2 illustrates the four different demand patterns:

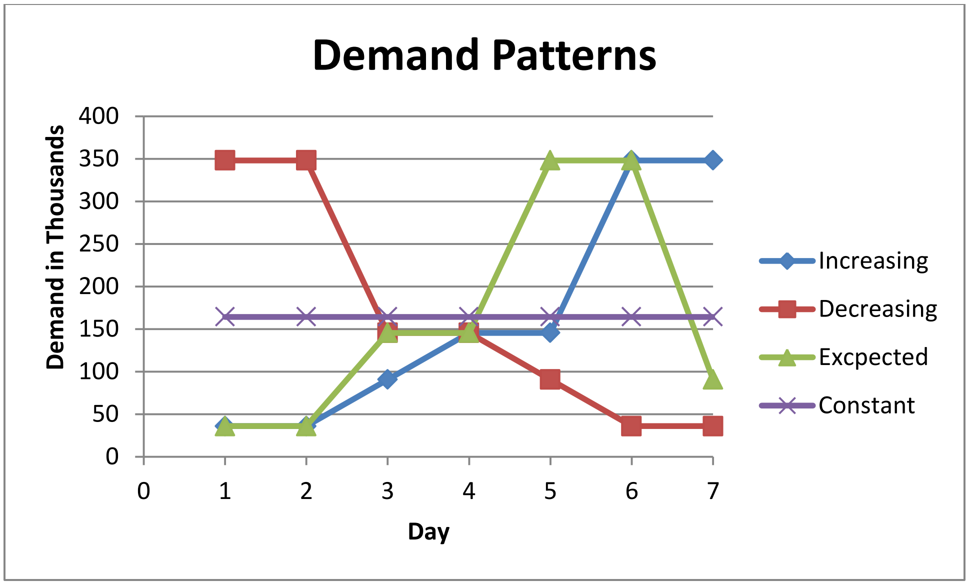

Figure 2: Total demand associated with demand patterns per day

Taking into consideration the isolated demand points, the possible demand to meet will be less than the total demand in Figure 2. Since we are using four different instances and four demand patterns, this will result in sixteen different possible scenarios of the magnitude of demand to meet. Table 3 summarizes the results.

Table 3: Connected demand per day for each instance

	Demand Pattern	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Instance 1	Increasing	32,176	32,176	84,307	135,807	135,745	327,467	327,467	1,075,206
	Decreasing	321,459	321,459	135,807	135,807	84,269	32,774	32,774	1,075,169
	Expected	32,176	32,176	135,807	135,807	327,467	327,467	84,269	1,071,342
	Constant	150,840	150,840	153,996	153,996	153,890	153,890	153,890	1,114,503
Instance 2	Increasing	34,140	34,140	87,729	140,655	140,655	338,592	338,592	1,114,503
	Decreasing	332,390	332,390	140,655	140,655	87,729	34,784	34,784	1,103,387
	Expected	34,140	34,140	140,655	140,655	338,592	338,592	87,729	1,114,503
	Constant	156,470	156,470	159,406	159,406	159,406	159,406	159,406	1,109,970
Instance 3	Increasing	32,408	32,408	82,689	132,952	133,271	322,662	322,662	1,059,052
	Decreasing	321,861	321,861	132,952	132,952	82,883	32,475	32,475	1,057,459
	Expected	32,408	32,408	132,952	132,952	322,662	322,662	82,883	1,058,927
	Constant	151,161	151,161	151,161	151,161	151,529	151,529	151,529	1,059,231
Instance 4	Increasing	32,963	32,963	83,650	134,134	135,435	327,969	327,969	1,075,083
	Decreasing	323,183	323,183	134,134	134,134	84,527	33,598	33,598	1,066,357
	Expected	32,963	32,963	134,134	134,134	327,969	327,969	84,529	1,074,661
	Constant	151,812	151,812	152,801	152,801	154,219	154,219	154,219	1,071,883

As it can be deduced from Table 3, changing the demand patterns affects the total connected demand that can be served. In general a decreasing pattern will have less connected demand as more demand points are isolated during the first few days when demand is high. The expected and increasing demand patterns have the highest connected demand as during day five and six when demand reaches its maximum, the number of connected demand points reaches its maximum as well. For example using road network instance one, the total connected demand using an increasing and expected demand patterns is around 1,075,000, while it is only 1,064,000 using a decreasing pattern.

5.1 Offline Results

In the offline approach, the decision maker knows all the information concerning the demand and road networks before making any decision. A commercial solver, CPLEX, was used to find a solution. However, due to the magnitude of the problem, most of the instances were not solved to optimality. Table 4 summarizes the average gap to optimality for a combination of POD capacity, demand pattern, and budget available:

Table 4 : Gap to optimality

Pod Capacity	Demand	High budget	Medium Budget	Low Budget
Medium	Constant	0.31%	0.44%	1.38%
	Decreasing	0.00%	0.10%	2.34%
	Increasing	0.01%	7.81%	8.97%
	Expected	1.09%	8.43%	8.64%
High	Constant	0.09%	0.42%	0.42%
	Decreasing	0.42%	1.19%	0.70%
	Increasing	0.40%	3.87%	6.55%
	Expected	0.36%	3.14%	3.91%

The solution of models using a high budget was closer to optimality. We are going to break the discussion of results into eight different sections based on the demand pattern and the PODs type.

5.1.1 Expected demand pattern

The instances used medium capacity PODs (10,000 capacity), with three different type of budget. The expected demand pattern starts with a low demand in day one and two, starts increasing in day three and four, reaches its maximum during day five and six, and starts decreasing during day seven.

5.1.1.1 Medium capacity PODs

Table 8 on appendix B gives a detailed look at the percent of demand served for each day and for the whole horizon. When using a high budget, the offline solution approach is able to serve all the demand in the four instances. The relatively high budget allows to open as many PODs as needed to serve the whole demand. The percent demand satisfied in Table 8 on appendix B is based on the demand associated with the connected PODs. When decreasing the budget to half, medium budget, an average of 86% of demand is served during the whole planning horizon. No demand is served during day one and day two, which constitutes only 6% of the total demand. The maximum demand served is reached on day five with an average of 94%. The difference between the demand served with high and medium budgets is only 14%, with a 6% not met during day one and two. When decreasing the budget to 92, there is a tendency to not serve any demand during day one and two as well, and serve only an average of 7.5% of demand during day three and four. On average, only 50% of the demand is served throughout the planning horizon. The percentage of demand served is greater than the percentage of demand points served which suggests that the offline approach serves the demand points that are associated with high demand.

Table 11 on appendix B summarizes the pattern of opening PODs. When using a high budget, all PODs are opened for the first time during day one, as the budget is enough to run them for the rest of the planning horizon. However, when using a medium and low budget, there is a tendency to wait until later days in the planning horizon to open the PODs. For the medium budget instances, most of the PODs are open for the first time during day three as demand starts to increase. For the low budget instances, the offline approach waits until day five when demand reaches its maximum. For both budgets, the maximum number of facilities open is reached on day five when demand reaches its maximum.

5.1.1.2 High capacity PODs

As described before, high capacity PODs have a capacity of 20,000. In our case we assumed that the cost associated with operating a high capacity PODs is twice as much as a medium capacity PODs. Due to the operating cost, fewer facilities will be operating throughout the planning horizon. The results obtained using high capacity PODs are close to the results using medium capacity PODs. On average, there is a two to three percent difference between the population served throughout the planning horizon using medium capacity and high capacity PODs. When using a high budget, the majority of demand associated with day one and two is satisfied, while using the other budget does not serve any demand during the first days. The number of demand served reaches its maximum during day five. Unlike when using the medium capacity PODs, not all PODs are open during the first day when using a high budget, due to the cost of operating them throughout the rest of the planning horizon. Two instances reach the maximum number of open PODs during the third day, while two others reach it during the fifth day. With a medium budget, similar to using medium capacity PODs, there is a tendency to wait until day three to open most of the PODs for the first time, and then the number of PODs open reaches its maximum on day five. In the instances with low budget, the solution approach tends to open a small number of PODs during day three, and then open most of the PODs during day five. The number of demand points serviced is slightly lower when using a high capacity PODs in comparison with medium capacity PODs. Tables 12, 13, and 14 summarize the results discussed.

5.1.2 Constant Demand Pattern

The constant demand pattern assumes that demand will be constant throughout the whole planning horizon.

5.1.2.1 Medium capacity PODs

Using a high budget with constant demand over the planning horizon, almost the whole connected demand is satisfied across the whole planning horizon for the four instances. Using a medium budget results in meeting an average of 97.5% of the total demand, even though the number of facilities open is twice as much for the high budget. This can be explained by the secondary objective of minimizing the travel distance, and the fact that some demand points account for a small percentages of the demand. While the high budget services almost 100% of demand points, the medium budget only services 91% of the demand points, which means that 9% of the demand points accounts for only 2% of the demand. Using a low budget will lead to meeting 72% of the demand and 48% of the demand points. With a constant demand, the offline approach solutions tend to open the maximum number of possible PODs during day one, and if budget allow open extra facilities at later days. With a constant demand, the approach is able to serve more demand in comparison with the expected demand. Tables 15, 16, and 17 in appendix B summarize the results.

5.1.2.2 High capacity PODs

When using high capacity PODs, less demand is being served in comparison with using medium capacity PODs. When using a high budget, the difference between the demands served using the two types of PODs is only 1%. The difference is much bigger between a medium and low budget. A decrease of 13% and 16% on the population served using medium and low budget respectively is noted between the two types of PODs. However, the solution approach keeps the same tendency concerning opening PODs as it opens the maximum possible number of PODs during day one, and depending on the remaining budget, it opens extra PODs later. The number of served demand points is fewer when using high capacity PODs in contrast with medium capacity. The percent of demand points served is significantly less than the percent demand served which means that the solution approach tends to service demand points with high demand associated with it first. Tables 18, 19, and 20 in appendix B summarize the results.

5.1.3 Increasing demand

The increasing demand pattern is close to the expected demand pattern except that demand on day seven of the expected pattern is now demand for day three and the rest of demand is shifted one day up.

5.1.3.1 Medium capacity PODs

As the other demand patterns, a high budget will result in meeting 100% of the demand and servicing 100% of the demand points by opening the maximum number of PODs since day one. When a medium budget is used, on average 87% of the connected demand is met. On day six, we reach the maximum demand met. The magnitude of day six and seven demand of the increasing demand pattern is equivalent on the magnitude of day five and six demand of the expected demand pattern. Most PODs are open for the first time during day four when demand starts increasing. The number of facilities open reaches its maximum on day six. The demand points percent served is less than the percent demand met. Using low budget results in opening most of the PODs for the first time during day six when demand reaches its maximum. No demand is served during the first three days, as the total demand associated with the three first days, only accounts for 14% of the total demand. In day four and five, few PODs are open to serve a small portion of the demand. Tables 21, 22, and 23 in appendix B summarize the results.

5.1.3.2 High capacity PODs

Unlike all the other demand patterns when using a high budget with high capacity PODs, not all the PODs are open for the first time during the first day. The number of PODs open reaches its maximum during day six. However, the offline solution approach is still able to meet 99% of the demand throughout the whole planning horizon. With a medium budget, most of the PODs open for the first time during day three, and the number of open PODs reach its maximum during day six when demand is at its maximum. The percent of demand served using high capacity PODs is slightly less than when using a medium capacity PODs. With a low budget, the average demand served is 56%. Most PODs start opening for the first time during day six. No demand is served during the first three days. In all cases, the percent of served demand points is less than the percent demand served. Tables 24, 25, and 26 in appendix B summarize the results.

5.1.4 Decreasing Demand

With the decreasing demand pattern, it is assumed that demand is high during the first two days and starts decreasing throughout the rest of the planning horizon to reach its minimum during day six and seven.

5.1.4.1 Medium capacity PODs

With all three types of budgets, all PODs are open during the first day when demand is at its maximum, and if the budget allows it, one more POD is open later (low budget). As expected, the solution tries to maximize the demand met during the first two days as it accounts for 60% of the total demand. With a low budget, during the first two days, servicing 8% of demand points leads to meet 34% of demand during these days. The total percent demand met when demand is decreasing is slightly less than the other patterns. Tables 27, 28, and 29 in appendix B summarize the results.

5.1.4.2 High capacity PODs

Like medium capacity PODs solutions, all the PODs are open during the first day as demand is at its maximum. An extra POD is open at a later period if budget allows it. High capacity PODs leads to a less percent demand served than medium capacity PODs. Tables 30, 31, and 32 in appendix B summarize the results.

5.1.5 General Patterns

Even though the solutions were different in each of the 96 instances, some general patterns were observed:

- In general, using medium capacity PODs leads to serving more demand than high capacity PODs. The difference is not large in most cases. This can be explained by the fact that two PODs of 10,000 can cover a larger area and thus more demand points, so the 20,000 PODs in most cases are not used to full capacity.

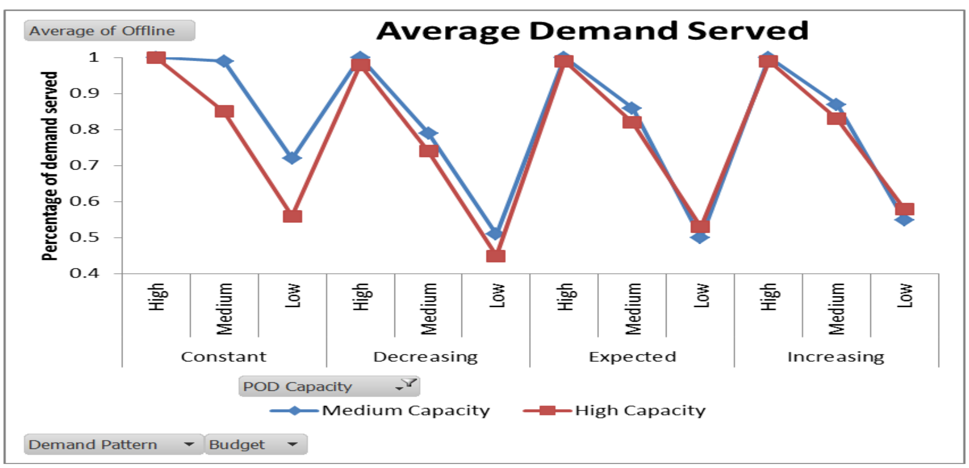

Figure 3: Demand served using medium and high capacity PODs

- The maximum number of PODs opened is reached during the day with the highest demand unless budget does not allow that (the decreasing pattern).
- The percent of demand points serviced is less than the percent of demand serviced as the solution approach tends to service demand points with higher demand.

- When the demand is constant, the demand serviced reaches its maximum, slightly greater than the increasing and expected demand pattern.
- When the demand pattern is decreasing; less demand is serviced in comparison with the other demand patterns. Less demand points are open throughout the whole planning horizon as all of them are open during day 1 and the cost associated with operating them for the rest of the planning horizon is high.

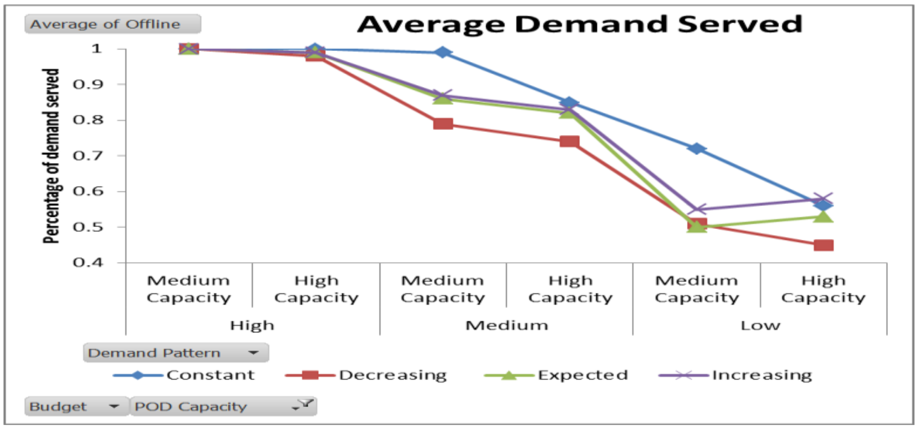

Figure 4: Demand served with the different demand patterns

The offline approach decision of either opening a POD or not is not necessarily driven by the total demand surrounding a POD. For each instance, the total demand that is possible to serve by each POD location was calculated. This demand is calculated based on the demand that each POD can serve within the 25-mile allowable distance. The possible demand for each day is the minimum of demand within the allowable distance and the POD capacity. Not all PODs associated with high demand were opened. Some PODs were ranked 117 based on the amount of demand surrounding the POD and still got opened seven out of twelve times using medium capacity POD with instance one. The decision made by CPLEX is far more comprehensive. The fact that each demand point can be serviced by multiple PODs makes ranking the PODs in a traditional way not significant. Once a POD services a demand point that can be serviced by a second POD, the possible demand that can be serviced with the second POD decreases.

5.2 Online Approach Results

The online model makes decisions on a day by day basis without knowing future period information. In this section, we are comparing how the choices made in the online approach solutions differ from those of the offline solutions. The majority of the PODs are open during day one for all instances, while in the offline solution the pattern at which PODs open depends on the demand pattern. The online approach does not get the benefit of knowing demand in the upcoming days which leads to opening the PODs as early as possible; therefore, if demand is increasing, the approach does not get the benefit of fulfilling a lot of demand, as it is restricted by the decisions of opening PODs at earlier days. In some instances, the decision of opening a POD is late as well. For example using a high budget with medium capacity PODs, the POD opened during day two could have been opened during day one without violating the budget constraint. From Table 5, we observe that the budget is not used to its fullest in all cases. With the medium capacity PODs, if the last POD was opened one day earlier, the solution would have been feasible. However, since the information concerning future demand is not known in advance, the solution approach decided that it is beneficial to save the budget for a later period. On the other hand, with the high capacity PODs, the unused budget (one or two units of budget) could not have been used due to the decisions made on day one. The operating cost of high capacity PODs is two units of budget at each period of the planning horizon.

Table 5: PODs opening pattern for online approach solutions

Budget	POD Capacity	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Cost
High	Medium	45	1	0	0	0	0	0	367
High	High	24	0	0	0	1	0	0	367
Medium	Medium	22	1	0	0	0	0	0	183
Medium	High	12	0	0	0	0	0	1	183
Low	Medium	11	0	0	0	0	1	0	91
Low	High	6	0	0	0	0	0	0	90

There is an average difference of 17% between the demand met using online and offline approach. However, the gap is around 22% when using a medium budget, and 13% when using a high budget. The gap is much smaller when the demand pattern is decreasing as the online approach solutions and offline solutions are following the same pattern of opening PODs. In an offline solution with a decreasing pattern, the PODs are open during the first days in order to fulfill the high demand during day one and two. The gap is much greater (21% average) when the demand is increasing, as opening PODs earlier leads to not meeting the high demand during later periods.

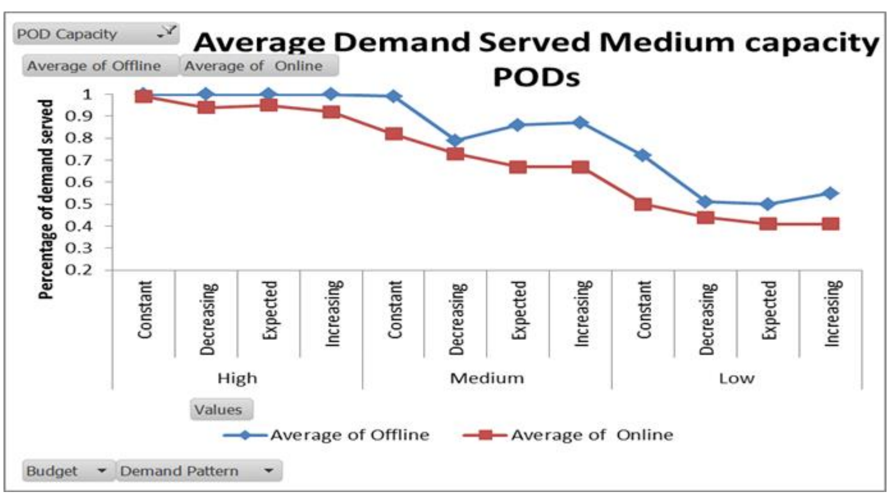

Figure 5: Demand served using online approach vs. offline approach with medium capacity PODs

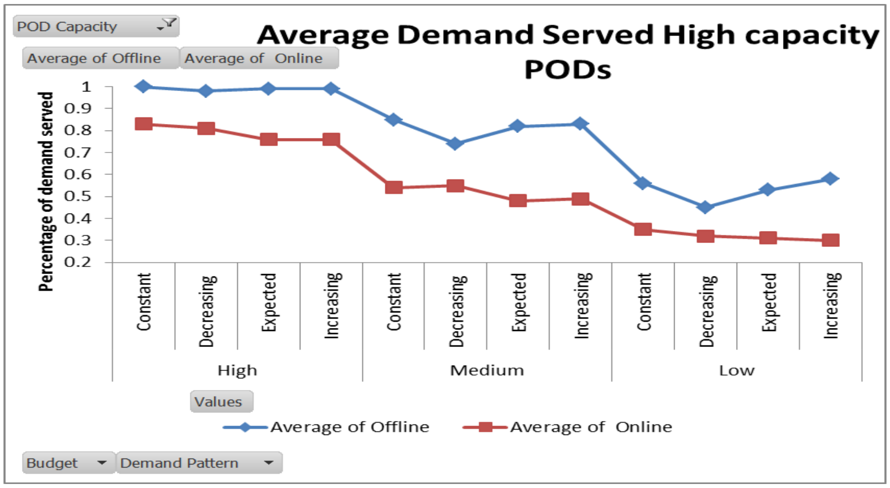

Figure 6: Demand served using online approach vs. offline approach with high capacity PODs

Interestingly, when demand is decreasing, using high capacity PODs and with a low budget, both the online and offline solutions are opening six PODs; but the percent of demand served is different. Moreover, only considering day one, the offline model solution still does much better than the online approach. The online approach strategy is based on ranking the demand points in an increasing order and then assigning them to the demand points in that order, while the offline model does not consider the order of the magnitude of demand at each demand point. Milburn et al. (2013) state that “the probability of opening a desired POD is determined by the ratio of the cost to open and operate the POD for the remainder of the horizon versus the distance from the demand location consideration to its desired POD” [2].

It seems that the online approach sacrifices servicing higher demand to service demand points with higher demand magnitude. The online solution serves less demand points than the offline solution. The online approach solution has the tendency to open the same demand points during the four instances while in the offline solution, the PODs opened are different from instance to instance. In the offline solutions, 120 PODs were opened at least once in comparison with 85 using the online approach. Only two of the non-opened PODs using the offline approach were not opened using the online approach. More interestingly, the fifth most opened POD using the online approach was never opened using an offline approach.

Table 6 : Comparison of demand serviced online vs. offline

Demand Pattern	Budget	POD Capacity	Online	Offline
Expected	High	Medium	95%	100%
Expected	High	High	76%	99%
Expected	Medium	Medium	67%	86%
Expected	Medium	High	48%	82%
Expected	Low	Medium	41%	50%
Expected	Low	High	31%	53%
Constant	High	Medium	99%	100%
Constant	High	High	83%	100%
Constant	Medium	Medium	82%	99%
Constant	Medium	High	54%	85%
Constant	Low	Medium	50%	72%
Constant	Low	High	35%	56%
Decreasing	High	Medium	94%	100%
Decreasing	High	High	81%	98%
Decreasing	Medium	Medium	73%	79%
Decreasing	Medium	High	55%	74%
Decreasing	Low	Medium	44%	51%
Decreasing	Low	High	32%	45%
Increasing	High	Medium	92%	100%
Increasing	High	High	76%	99%
Increasing	Medium	Medium	67%	87%
Increasing	Medium	High	49%	83%
Increasing	Low	Medium	41%	55%
Increasing	Low	High	30%	58%

6. Conclusion/Future Work

Having a good response plan after a major earthquake is extremely complicated due to the high uncertainty associated with the road network, demand locations and magnitude. An online disaster relief model making decisions about where to locate points of distribution based on real time information was developed. The model mimics the decisions that a decision maker has to make after an earthquake given limited information. A mixed integer program was created to consider what an optimal solution with perfect information would be, and to be able to judge the quality of the online solution. The “Models for disaster relief shelter location and supply routing” suggested conducting analysis on the impact of the budget level and PODs operating cost on the solution of both approaches. The analysis was conducted in addition to studying the impact of having different demand patterns and different POD capacities.

The offline solution, or the perfect information solution, changes the pattern of opening PODs depending on the demand pattern. It seems that it is better to open PODs as early as possible when the demand is decreasing or constant, while it is better to wait for later periods for the expected and decreasing demand patterns. In general, the budget had an effect on the number of facilities open, but not the pattern at which PODs are open. With a high budget, the solution tends to open the maximum possible number of facilities during day one, which leads to a high coverage of nearly 100%. However with the two limiting budgets medium and low, the solution follows the same pattern of opening the PODs. In general, using medium capacity PODs (Capacity 10,000) leads to satisfying more demand than using high capacity PODs (Capacity 20,000). Varying the barriers did not have an impact on the pattern of opening the facilities; however, it affected which facilities to open for both the online and offline solution.

The online approach solution was less vulnerable to changing the parameters. In all instances, the model solution opened the maximum possible number of PODs during the first day of the planning horizon. Maximizing the demand served during day one by opening the maximum number of PODs during day one is attractive from an online perspective as no future information is known. However, the decision leads to not satisfying higher demand during future periods in case of an expected or increasing demand pattern. On average, the online solution served 17% less demand than the offline solution.

In some cases, the online and offline model solutions opened the same number of facilities during day one, however the demand served during day one was much higher in favor of the offline solution. Future work might be done to reconsider the POD opening strategy used on the online approach which is based on ranking the demand points based on the magnitude of demand associated with them. Another approach that might lead to better results is to rank the PODs based on the demand that might be served, and once one of the PODs is open and a set of demand points I_1 are assigned to it, dynamically recalculate the demand associated with the remaining PODs after taking off the demand associated with set of demand points I_1, and repeat the same action until the number of PODs that needs to be opened are already operating. More constraints might be added to opening PODs during day one, such as the demand associated with it.

References

1. Federal Emergency Management Agency. 2008. IS-26 guide to Points of Distribution. Available from http://training.fema.gov/EMIWeb/IS/is26.asp.

2. Milburn, A.B., Rainwater, C.E., Boudhoum, O,Young , S. 2013. Models for disaster relief shelter location and supply routing.Mack Blackwell National Rural Transportation Center. Available from http://trid.trb.org/view.aspx?id=1246217

3. Elnashai AS, Cleveland LJ, Jefferson T and Harrald J. 2009. Impact of New Madrid SeismicZone earthquakes on the central USA volume I. MAE Center Report No. 09-03. Available from http://mae.cee.illinois.edu/publications/2009/09-03.htm.

4. Celik M, Ergun O, Johnson B, Keskinocak P, Lorca A, Pekgun P and Swann J. 2012. Humanitarian logistics. InTutorials in Operations Research: New Directions in Informatics,Optimization, Logistics, and Production. Hanover, MD: Institute for Operations Research and the Management Sciences.

5. Yushimito W, Jaller M and Ukkusuri S. 2012. A Voronoi-Based heuristic algorithm for locating distribution centers in Disasters. Networks and Spatial Economics 10(3), p. 1-19.

6. Campbell AM and Jones PC. 2011. Prepositioning supplies in preparation for disasters. European Journal of Operational Research 209, p. 156-165.

7. Rawls CG and Turnquist MA. 2010. Pre-positioning of emergency supplies for disaster response. Transportation Research Part B: Methodological 44(4), p. 521-534.

8. Jaller M and Holguín-Veras J. 2011. Locating points of distribution with social costs considerations. Submitted to the 90th Transportation Research Board Annual Meeting.

9. Balcik B and Beamon BM. 2008. Facility location in humanitarian relief. International Journal of Logistics: Research and Applications 11(2), p. 101-121.

10. Perez N, Holguín-Veras J, Mitchell JE and Sharkey TC. 2010. Integrated vehicle routing problem with explicit consideration of social costs in humanitarian logistics. Submitted.

11. Balcik B, Beamon BM and Smilowitz K. 2008. Last mile distribution in humanitarian relief. Journal of Intelligent Transportation Systems 12(2), p. 51-63.

12. De la Torre LE, Dolinskaya IS and Smilowitz KR. 2012. Disaster relief routing: integrating research and practice. Socio-Economic Planning Sciences 46(1), p. 88-97.

13. Hagan, C. 2010. County Points of Distribution (PODs) Course. Florida Department of Emergency Management. Available from http://www.floridadisater.org.

14. Educationbug. 2012. Public schools by county. Available from http://arkansas.educationbug.org/public-schools/

15. U.S. Census Bureau. 2003. Arkansas: 2000 population and housing unit counts. Retrieved from http://www.census.gov/prod/cen2000/phc-3-5.pdf.

16. Holguín-Veras, J. and Jaller, M. 2012. ”Immediate Resource Requirements after Hurricane Katrina.” Nat. Hazards Rev., 13(2), 117–131.

Appendix A: Models

The offline Model

Table 7: Model elements

Item	Type	Description
X_{ijt}	binary variable	equals 1 if demand point *i* is assigned to POD *j* in planning period *t* and 0 otherwise
A_{ijt}	continuous variable with range [0,1]	percentage of demand of point *i* satisfied by POD *j* in period *t*
Z_{jt}	binary decision variable	equals 1 if POD opened at potential POD location *j* in period *t* and 0 otherwise
Y_{jt}	binary decision variable	equals 1 if POD *j* operates in period *t* and 0 otherwise
d_{it}	input parameter	demand of point *i* in period *t*
h_{ijt}	input parameter	length of shortest path from *i* to *j* in G_t
C_F	input parameter	fixed cost to open a POD
c_o	input parameter	cost per period to operate a POD
B	input parameter	total budget for opening and operating PODs
Q	input parameter	POD capacity
D	input parameter	maximum allowable distance between a demand point and its assigned POD location
M	input parameter	sufficiently large constant

"The objective is to maximize the total demand served during the planning horizon. A secondary objective is to minimize the distance between demand points and their assigned POD locations using the available road network in each period. Constraints (1) are used to ensure each demand point is served by at most one POD. Constraints (2)-(4) control the opening and operating of PODs. Constraints (2) ensure that an opened POD will continue to operate until the end of the planning horizon. Constraints (3) ensure that unopened PODs cannot be operated, and constraints (4) ensure that each POD location can be opened at most once. Constraints (5) are used to enforce that once a portion of demand from a demand point has been assigned to a POD, the same POD will continue to satisfy at least that quantity of demand from the point for the remainder of the planning horizon. Constraints (6) ensure that demand cannot be assigned to

PODs in periods they are not operating. Constraint (7) ensures the total budget for opening and operating PODs is not exceeded, and constraints (8) ensure the capacities of operating PODs are not exceeded. Constraints (9) enforce the maximum allowable distance between a demand point and its assigned POD location using the accessible road network in each period."

$$\text{Maximize } \sum_1^i \sum_1^j \sum_1^t (d_{it}\, \mathrm{A}_{ijt} - M h_{ijt} X_{ijt})$$

$$[1] \quad \sum_1^j X_{ijt} \leq 1 \quad \forall\, \mathrm{i} \in I, \forall\, \mathrm{t} \in T\ ,$$

$$[2] \quad Y_{jt} \geq \ \sum_1^t Z_{jt} \quad \forall\, \mathrm{j} \in J, \forall\, \mathrm{t} \in T,$$

$$[3] \quad Y_{jt} \leq \ \sum_1^t Z_{jt} \quad \forall\, \mathrm{j} \in J, \forall\, \mathrm{t} \in T,$$

$$[4] \quad \sum_1^t Z_{jt} \leq 1 \quad \forall\, \mathrm{j} \in J,$$

$$[5] \quad A_{t-1} \leq A_t \quad \forall\, \mathrm{i} \in I, \forall\, \mathrm{j} \in J, \forall\, \mathrm{t} \in (2..t),$$

$$[6] \quad A_{ijt} \leq \ X_{ijt} \quad \forall\, \mathrm{i} \in I, \forall\, \mathrm{j} \in J, \forall\, \mathrm{t} \in T,$$

$$[7] \quad \sum_1^j \sum_1^t (Z_{jt}\, C_F \ + Y_{jt} c_{oj}) \leq B,$$

$$[8] \quad \sum_1^i A_{ijt} d_{it} \leq Q Y_{jt} \ \forall\, \mathrm{j} \in J, \forall\, \mathrm{t} \in T,$$

$$[9] \quad h_{ijt} X_{ijt} \leq D \quad \forall\, \mathrm{i} \in I, \forall\, \mathrm{j} \in J, \forall\, \mathrm{t} \in T.$$

<u>The online solution approach</u>

The detailed description of our online algorithm is presented as follows.

<u>Notation:</u>

Let D_t be the set of available demand points in period t

Let b be the remaining budget available in each period

Let g_{pt} be the amount of remaining capacity at POD p in period t

Let F_i be the set of PODs located within 25 miles of demand location i

Let A_{pt} be the demand points assigned to POD p in period t

Let M_p be the set of minimum levels in which we must satisfy those demand points assigned to POD p

Let m_k be the minimum level at with demand point k can be satisfied

Online Algorithm:

<u>Step 0 (Initialization):</u> $A_{pt} = \emptyset$, $S_{pt} = \emptyset$ for all $p \in P$ and $t \in T$. Sort D_t in non-increasing order h_{it} for all $t \in T$. Set $t' = 1$.

<u>Step 1 (Satisfy established demand):</u> If $t' > T$, STOP, else initialize $g_{pt'} = G$ for all $p \in P$ and $b = B$. If $t' = 1$, continue to Step 2. Else, for all $p \in P$, first update $A_{pt'} = A_{p(t'-1)}, g_{pt'} = g_{pt'} - \sum_{k=1}^{|M_p|} m_k$ and then continue to Step 2.

<u>Step 2 (Consider new demand):</u> Set $D_{t'} = D_{t'}/\{\cup_{p \in P} A_{pt'}\}$ and i' to be the first demand point in $D_{t'}$. If $D_{t'} = \emptyset$, set $t' = t' + 1$ and return to Step 1. Else, if $D_{t'} \neq \emptyset$, let $\bar{p} = \text{argmin}_{p \in F_{i'}} d_{i'p}$. If $A_{\bar{p}t'} \neq \emptyset$ and $g_{\bar{p}t'} > 0$, continue to Step 2a. If $A_{\bar{p}t'} \neq \emptyset$ and $g_{\bar{p}t'} = 0$, set $F_{i'} = F_{i'}/\bar{p}$ and repeat Step 2. If $A_{\bar{p}t'} = \emptyset$, continue to Step 2b.

<u>Step 2a (Assign new demand to open facility):</u> Assign i' to $\bar{p}$ by updating $A_{\bar{p}t'} = A_{\bar{p}t'} \cup i'$. Set $m_{i'} = \min\{g_{\bar{p}t'}, d_{i't}\}$. Update the remaining capacity of the POD to be $g_{\bar{p}t'} = g_{\bar{p}t'} - m_{i'}$. Return to Step 2.

<u>Step 2b (Consider opening desired POD):</u> If $\sum_{t=t'}^{T} c_0 + C_F > b$, set $F_{i'} = F_{i'} \backslash \bar{p}$ and return to Step 2. Else, generate r = U(0,1). If r > $\frac{\sum_{t=t'}^{T} c_0 + C_F}{h_{i'\bar{p}}}$, set $F_{i'} = F_{i'} \backslash \bar{p}$ and return to Step 2. Otherwise, $A_{\bar{p}t'} = A_{\bar{p}t'} \cup i'$. Set $m_{i'} = \min\{Q, d_{i't}\}$, $b = b - \sum_{t=t'}^{T} c_0 + C_F$ and $g_{\bar{p}t'} = g_{\bar{p}t'} - m_{i'}$. Return to Step 2.” [2]

Appendix B: Results

Table 8 : Demand fulfilled offline Results for expected demand pattern using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Planning Horizon
1	High	100%	100%	100%	100%	100%	100%	100%	100%
1	Medium	0%	0%	84%	89%	94%	94%	99%	87%
1	Low	0%	0%	7%	7%	67%	67%	92%	50%
2	High	100%	100%	100%	100%	100%	100%	100%	100%
2	Medium	0%	0%	81%	81%	94%	94%	97%	85%
2	Low	0%	0%	7%	7%	65%	65%	92%	49%
3	High	100%	100%	100%	100%	100%	100%	100%	100%
3	Medium	0%	0%	85%	85%	94%	94%	97%	86%
3	Low	0%	0%	8%	8%	68%	68%	90%	51%
4	High	100%	100%	100%	100%	100%	100%	100%	100%
4	Medium	0%	0%	79%	83%	94%	94%	96%	85%
4	Low	0%	0%	8%	8%	67%	67%	87%	50%

Table 9 : PODs opening pattern for expected demand using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	46	0	0	0	0	0	0
1	Medium	0	0	27	2	3	0	0
1	Low	0	0	2	0	20	0	0
2	High	46	0	0	0	0	0	0
2	Medium	0	0	26	0	7	0	0
2	Low	0	0	2	0	20	0	0
3	High	46	0	0	0	0	0	0
3	Medium	0	0	28	0	4	0	0
3	Low	0	0	2	0	20	0	0
4	High	46	0	0	0	0	0	0
4	Medium	0	0	25	6	0	0	0
4	Low	0	0	2	0	20	0	0

Table 10 : Demand points serviced offline results for expected demand pattern using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	100%	100%	99%	99%	100%	100%	100%
1	Medium	0%	0%	64%	75%	86%	86%	86%
1	Low	0%	0%	5%	5%	31%	31%	31%
2	High	99%	99%	100%	100%	100%	100%	100%
2	Medium	0%	0%	64%	64%	86%	87%	87%
2	Low	0%	0%	5%	5%	44%	44%	44%
3	High	100%	100%	100%	100%	100%	100%	100%
3	Medium	0%	0%	74%	74%	89%	89%	89%
3	Low	0%	0%	3%	3%	39%	39%	39%
4	High	99%	99%	99%	99%	100%	100%	100%
4	Medium	0%	0%	62%	70%	90%	90%	90%
4	Low	0%	0%	5%	5%	39%	39%	39%

Table 11 : Demand fulfilled offline Results for expected demand pattern using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Planning Horizon
1	High	89%	89%	99%	99%	100%	100%	100%	99%
1	Medium	0%	0%	78%	81%	90%	90%	93%	82%
1	Low	0%	0%	15%	15%	72%	72%	78%	54%
2	High	94%	95%	99%	99%	99%	99%	99%	99%
2	Medium	0%	0%	78%	81%	90%	90%	92%	82%
2	Low	0%	0%	14%	14%	70%	70%	78%	52%
3	High	89%	91%	99%	99%	99%	99%	99%	99%
3	Medium	0%	0%	78%	82%	91%	91%	91%	82%
3	Low	0%	0%	14%	14%	73%	73%	76%	54%
4	High	90%	90%	98%	98%	99%	99%	100%	99%
4	Medium	0%	0%	76%	80%	89%	89%	90%	81%
4	Low	0%	0%	14%	14%	70%	70%	76%	52%

Table 12 : PODs opening pattern for expected demand using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	17	0	9	0	2	0	0
1	Medium	0	0	14	1	3	0	0
1	Low	0	0	2	0	10	0	0
2	High	20	1	5	0	0	0	0
2	Medium	0	0	14	1	3	0	0
2	Low	0	0	2	0	10	0	0
3	High	18	1	7	0	1	0	0
3	Medium	0	0	14	1	3	0	0
3	Low	0	0	2	0	10	0	0
4	High	18	0	7	0	3	0	0
4	Medium	0	0	14	1	3	0	0
4	Low	0	0	2	0	10	0	0

Table 13 : Demand points serviced offline results for expected demand pattern using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	58%	58%	94%	94%	97%	97%	97%
1	Medium	0%	0%	67%	71%	79%	79%	79%
1	Low	0%	0%	4%	4%	55%	55%	55%
2	High	72%	80%	96%	96%	96%	96%	96%
2	Medium	0%	0%	61%	66%	75%	75%	75%
2	Low	0%	0%	5%	5%	46%	46%	46%
3	High	60%	63%	93%	93%	97%	97%	97%
3	Medium	0%	0%	63%	68%	82%	82%	82%
3	Low	0%	0%	4%	4%	47%	47%	47%
4	High	61%	61%	94%	94%	97%	97%	97%
4	Medium	0%	0%	50%	58%	77%	77%	77%
4	Low	0%	0%	4%	4%	52%	52%	52%

Table 14 : Demand fulfilled offline Results for constant demand pattern using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Planning Horizon
1	High	100%	100%	100%	100%	100%	100%	100%	100%
1	Medium	98%	98%	97%	97%	98%	98%	98%	98%
1	Low	65%	65%	74%	74%	74%	74%	74%	71%
2	High	100%	100%	100%	100%	100%	100%	100%	100%
2	Medium	98%	98%	98%	98%	98%	98%	98%	98%
2	Low	72%	72%	72%	72%	77%	77%	77%	74%
3	High	100%	100%	100%	100%	100%	100%	100%	100%
3	Medium	97%	97%	97%	97%	97%	97%	97%	97%
3	Low	71%	71%	71%	71%	74%	74%	81%	73%
4	High	100%	100%	100%	100%	100%	100%	100%	100%
4	Medium	97%	97%	97%	97%	98%	98%	98%	97%
4	Low	68%	68%	68%	68%	72%	72%	72%	70%

Table 15 : PODs opening pattern for constant demand using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	46	0	0	0	0	0	0
1	Medium	23	0	0	0	0	0	0
1	Low	10	0	2	0	0	0	0
2	High	46	0	0	0	0	0	0
2	Medium	23	0	0	0	0	0	0
2	Low	11	0	0	0	1	0	0
3	High	46	0	0	0	0	0	0
3	Medium	23	0	0	0	0	0	0
3	Low	11	0	0	0	1	0	0
4	High	46	0	0	0	0	0	0
4	Medium	23	0	0	0	0	0	0
4	Low	11	0	0	0	1	0	0

Table 16 : Demand points serviced offline results for constant demand pattern using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	100%	100%	100%	100%	100%	100%	100%
1	Medium	91%	91%	91%	91%	91%	91%	91%
1	Low	42%	42%	52%	52%	52%	52%	52%
2	High	100%	100%	100%	100%	100%	100%	100%
2	Medium	90%	90%	91%	91%	91%	91%	91%
2	Low	38%	38%	38%	38%	42%	42%	42%
3	High	100%	100%	100%	100%	100%	100%	100%
3	Medium	88%	88%	88%	88%	90%	90%	90%
3	Low	49%	49%	49%	49%	54%	54%	54%
4	High	100%	100%	99%	99%	100%	100%	100%
4	Medium	93%	93%	92%	92%	93%	93%	93%
4	Low	43%	43%	43%	43%	45%	45%	45%

Table 17 : Demand fulfilled offline Results for constant demand pattern using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Planning Horizon
1	High	99%	99%	99%	99%	99%	99%	99%	99%
1	Medium	80%	80%	84%	84%	85%	85%	88%	84%
1	Low	51%	51%	59%	59%	60%	66%	7%	50%
2	High	99%	99%	99%	99%	99%	99%	99%	99%
2	Medium	86%	86%	88%	88%	89%	89%	91%	88%
2	Low	52%	52%	54%	61%	68%	68%	68%	60%
3	High	99%	99%	99%	99%	99%	99%	99%	99%
3	Medium	82%	82%	82%	82%	83%	83%	86%	83%
3	Low	55%	55%	55%	55%	56%	56%	56%	55%
4	High	99%	99%	99%	99%	99%	99%	99%	99%
4	Medium	84%	84%	84%	84%	84%	84%	86%	85%
4	Low	60%	60%	59%	59%	59%	59%	59%	59%

Table 18 : PODs opening pattern for constant demand using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	24	0	0	0	1	0	0
1	Medium	12	0	0	0	0	0	1
1	Low	5	0	1	0	0	1	0
2	High	24	0	0	0	1	0	0
2	Medium	12	0	0	0	0	0	1
2	Low	5	0	0	1	1	0	0
3	High	24	0	0	0	1	0	0
3	Medium	12	0	0	0	0	0	1
3	Low	6	0	0	0	0	0	0
4	High	24	0	0	0	1	0	0
4	Medium	12	0	0	0	0	0	1
4	Low	6	0	0	0	0	0	0

Table 19 : Demand points serviced offline results for constant demand pattern using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	95%	95%	95%	95%	96%	96%	96%
1	Medium	69%	69%	70%	70%	71%	71%	71%
1	Low	37%	37%	42%	42%	42%	45%	45%
2	High	95%	95%	96%	96%	96%	96%	96%
2	Medium	68%	68%	68%	68%	69%	69%	69%
2	Low	37%	37%	37%	41%	43%	43%	43%
3	High	95%	95%	95%	95%	97%	97%	97%
3	Medium	67%	67%	68%	68%	69%	69%	69%
3	Low	40%	40%	40%	40%	41%	41%	41%
4	High	94%	94%	94%	94%	95%	95%	95%
4	Medium	71%	71%	71%	71%	71%	71%	71%
4	Low	43%	43%	43%	43%	44%	44%	44%

Table 20 : Demand fulfilled offline Results for increasing demand pattern using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Planning Horizon
1	High	100%	100%	100%	100%	100%	100%	100%	100%
1	Medium	0%	0%	68%	92%	92%	97%	97%	87%
1	Low	0%	0%	0%	8%	11%	88%	88%	56%
2	High	100%	100%	100%	100%	100%	100%	100%	100%
2	Medium	0%	0%	67%	85%	90%	97%	97%	87%
2	Low	0%	0%	0%	4%	4%	87%	88%	54%
3	High	100%	100%	100%	100%	100%	100%	100%	100%
3	Medium	0%	0%	62%	93%	93%	96%	96%	87%
3	Low	0%	0%	0%	15%	15%	86%	86%	56%
4	High	100%	100%	100%	100%	100%	100%	100%	100%
4	Medium	0%	0%	66%	86%	90%	96%	96%	86%
4	Low	0%	0%	0%	7%	11%	87%	87%	55%

Table 21 : PODs opening pattern for increasing demand using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	46	0	0	0	0	0	0
1	Medium	0	0	20	11	0	3	0
1	Low	0	0	0	2	1	26	0
2	High	46	0	0	0	0	0	0
2	Medium	0	0	20	8	3	4	0
2	Low	0	0	0	1	0	29	0
3	High	46	0	0	0	0	0	0
3	Medium	0	0	18	14	0	2	0
3	Low	0	0	0	4	0	24	0
4	High	46	0	0	0	0	0	0
4	Medium	0	0	19	10	2	4	0
4	Low	0	0	0	2	1	26	0

Table 22 : Demand points serviced offline results for increasing demand pattern using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	100%	100%	100%	100%	100%	100%	100%
1	Medium	0%	0%	41%	77%	77%	91%	91%
1	Low	0%	0%	0%	5%	6%	69%	69%
2	High	99%	99%	100%	100%	100%	100%	100%
2	Medium	0%	0%	41%	70%	81%	92%	92%
2	Low	0%	0%	0%	2%	2%	63%	63%
3	High	100%	100%	100%	100%	100%	100%	100%
3	Medium	0%	0%	39%	82%	82%	91%	91%
3	Low	0%	0%	0%	6%	6%	69%	69%
4	High	100%	100%	99%	99%	100%	100%	100%
4	Medium	0%	0%	35%	71%	78%	95%	95%
4	Low	0%	0%	0%	4%	5%	74%	74%

Table 23 : Demand fulfilled offline Results for increasing demand pattern using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Planning Horizon
1	High	91%	92%	98%	99%	99%	100%	100%	99%
1	Medium	0%	0%	64%	81%	88%	94%	94%	84%
1	Low	0%	0%	0%	28%	48%	80%	80%	58%
2	High	93%	93%	99%	99%	99%	100%	100%	99%
2	Medium	0%	0%	58%	83%	87%	94%	94%	83%
2	Low	0%	0%	0%	35%	40%	80%	80%	58%
3	High	90%	92%	98%	99%	99%	100%	100%	99%
3	Medium	0%	0%	59%	84%	89%	94%	94%	84%
3	Low	0%	0%	0%	28%	48%	81%	81%	59%
4	High	92%	93%	98%	98%	99%	100%	100%	99%
4	Medium	0%	0%	59%	83%	86%	93%	93%	82%
4	Low	0%	0%	0%	33%	40%	79%	79%	57%

Table 24 : PODs opening pattern for increasing demand using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	18	1	6	1	0	2	0
1	Medium	0	0	10	5	2	3	0
1	Low	0	0	0	4	3	7	0
2	High	19	0	6	0	1	2	0
2	Medium	0	0	9	7	1	3	0
2	Low	0	0	0	5	1	8	0
3	High	18	1	6	1	0	2	0
3	Medium	0	0	9	7	1	3	0
3	Low	0	0	0	4	3	7	0
4	High	19	1	5	0	0	3	0
4	Medium	0	0	9	7	1	3	0
4	Low	0	0	0	5	1	8	0

Table 25 : Demand points serviced offline results for increasing demand pattern using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	60%	65%	93%	94%	95%	97%	97%
1	Medium	0%	0%	36%	66%	75%	84%	84%
1	Low	0%	0%	0%	10%	22%	65%	65%
2	High	66%	66%	95%	95%	96%	98%	98%
2	Medium	0%	0%	28%	66%	72%	83%	83%
2	Low	0%	0%	0%	14%	16%	58%	58%
3	High	69%	69%	92%	94%	96%	98%	98%
3	Medium	0%	0%	34%	74%	82%	86%	86%
3	Low	0%	0%	0%	11%	25%	69%	69%
4	High	66%	67%	94%	94%	95%	98%	98%
4	Medium	0%	0%	29%	65%	73%	83%	83%
4	Low	0%	0%	0%	12%	16%	59%	59%

Table 26 : Demand fulfilled offline Results for decreasing demand pattern using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Planning Horizon
1	High	100%	100%	100%	100%	100%	100%	100%	100%
1	Medium	69%	69%	96%	96%	96%	96%	96%	80%
1	Low	34%	34%	74%	74%	82%	86%	86%	51%
2	High	100%	100%	100%	100%	100%	100%	100%	100%
2	Medium	67%	67%	96%	96%	97%	97%	97%	79%
2	Low	33%	33%	74%	74%	80%	82%	82%	50%
3	High	100%	100%	100%	100%	100%	100%	100%	100%
3	Medium	68%	68%	96%	96%	96%	96%	96%	79%
3	Low	34%	34%	75%	75%	79%	80%	80%	51%
4	High	100%	100%	100%	100%	100%	100%	100%	100%
4	Medium	69%	69%	94%	94%	94%	94%	94%	78%
4	Low	34%	34%	73%	73%	79%	81%	81%	50%

Table 27 : PODs opening pattern for decreasing demand using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	46	0	0	0	0	0	0
1	Medium	23	0	0	0	0	0	0
1	Low	11	0	0	0	1	0	0
2	High	46	0	0	0	0	0	0
2	Medium	23	0	0	0	0	0	0
2	Low	11	0	0	0	1	0	0
3	High	46	0	0	0	0	0	0
3	Medium	23	0	0	0	0	0	0
3	Low	11	0	0	0	1	0	0
4	High	46	0	0	0	0	0	0
4	Medium	23	0	0	0	0	0	0
4	Low	11	0	0	0	1	0	0

Table 28: Demand points serviced offline results for decreasing demand pattern using medium capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	100%	100%	100%	100%	100%	100%	100%
1	Medium	41%	41%	88%	88%	89%	89%	89%
1	Low	8%	8%	51%	51%	60%	60%	60%
2	High	100%	100%	100%	100%	100%	100%	100%
2	Medium	49%	49%	89%	89%	90%	90%	90%
2	Low	7%	7%	48%	48%	56%	56%	56%
3	High	100%	100%	100%	100%	100%	100%	100%
3	Medium	49%	49%	91%	91%	91%	91%	91%
3	Low	9%	9%	59%	59%	64%	64%	64%
4	High	100%	100%	99%	99%	100%	100%	100%
4	Medium	46%	46%	88%	88%	88%	88%	88%
4	Low	7%	7%	60%	60%	64%	64%	64%

Table 29 : Demand fulfilled offline Results for decreasing demand pattern using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Planning Horizon
1	High	98%	98%	98%	98%	99%	99%	100%	98%
1	Medium	69%	69%	80%	80%	80%	80%	84%	74%
1	Low	37%	37%	57%	57%	59%	61%	61%	45%
2	High	98%	98%	98%	98%	99%	99%	99%	98%
2	Medium	70%	70%	78%	78%	78%	78%	83%	73%
2	Low	36%	36%	57%	57%	58%	64%	64%	45%
3	High	97%	97%	99%	99%	99%	99%	99%	98%
3	Medium	71%	71%	80%	80%	80%	78%	83%	74%
3	Low	37%	37%	55%	55%	55%	54%	54%	44%
4	High	98%	98%	97%	97%	99%	99%	99%	98%
4	Medium	71%	71%	76%	76%	76%	76%	81%	73%
4	Low	37%	37%	58%	58%	59%	65%	65%	46%

Table 30 : PODs opening pattern for decreasing demand using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	24	0	0	0	1	0	0
1	Medium	12	0	0	0	0	0	1
1	Low	6	0	0	0	0	0	0
2	High	24	0	0	0	1	0	0
2	Medium	12	0	0	0	0	0	1
2	Low	6	0	0	0	0	0	0
3	High	24	0	0	0	1	0	0
3	Medium	12	0	0	0	0	0	1
3	Low	6	0	0	0	0	0	0
4	High	24	0	0	0	1	0	0
4	Medium	12	0	0	0	0	0	1
4	Low	6	0	0	0	0	0	0

Table 31 : Demand points serviced offline results for decreasing demand pattern using high capacity PODs

Instance	Budget	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	High	92%	92%	92%	92%	93%	93%	93%
1	Medium	52%	52%	69%	69%	70%	70%	70%
1	Low	10%	10%	37%	37%	38%	38%	38%
2	High	93%	93%	94%	94%	95%	95%	95%
2	Medium	44%	44%	61%	61%	61%	61%	61%
2	Low	11%	11%	27%	27%	27%	27%	27%
3	High	90%	90%	93%	93%	96%	96%	96%
3	Medium	40%	40%	67%	67%	69%	69%	69%
3	Low	11%	11%	41%	41%	42%	42%	42%
4	High	94%	94%	93%	93%	95%	95%	95%
4	Medium	51%	51%	61%	61%	62%	62%	62%
4	Low	12%	12%	33%	33%	34%	34%	34%

Appendix C: Data

Table 32 : Percent demand per county for expected demand pattern

	Demand Percentage						
County	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Arkansas	3.60%	3.60%	20.60%	20.60%	60.30%	60.30%	12.10%
Clay	6.10%	6.10%	30.73%	30.73%	65.36%	65.36%	18.42%
Craighead	7.65%	7.65%	27.88%	27.88%	63.94%	63.94%	17.76%
Crittenden	10.23%	10.23%	31.57%	31.57%	65.78%	65.78%	20.90%
Cross	7.47%	7.47%	31.12%	31.12%	65.56%	65.56%	19.29%
Greene	6.86%	6.86%	27.29%	27.29%	63.64%	63.64%	17.07%
Independence	3.41%	3.41%	16.25%	16.25%	58.13%	58.13%	9.83%
Jackson	6.25%	6.25%	30.14%	30.14%	65.07%	65.07%	18.20%
Lawrence	4.12%	4.12%	25.12%	25.12%	62.56%	62.56%	14.62%
Lee	7.37%	7.37%	37.02%	37.02%	68.51%	68.51%	22.19%
Mississippi	12.15%	12.15%	31.97%	31.97%	65.99%	65.99%	22.06%
Monroe	4.34%	4.34%	25.04%	25.04%	62.52%	62.52%	14.69%
Phillips	4.69%	4.69%	24.92%	24.92%	62.46%	62.46%	14.80%
Poinsett	10.70%	10.70%	30.70%	30.70%	65.35%	65.35%	20.70%
Prairie	3.65%	3.65%	20.41%	20.41%	60.21%	60.21%	12.03%
Randolph	1.60%	1.60%	20.93%	20.93%	60.47%	60.47%	11.27%
St. Francis	6.82%	6.82%	35.69%	35.69%	67.84%	67.84%	21.25%
White	1.36%	1.36%	14.39%	14.39%	57.20%	57.20%	7.88%
Woodruff	7.28%	7.28%	33.67%	33.67%	66.83%	66.83%	20.47%

Table 33 : Percent demand per county for the increasing demand pattern

	Demand Percentage						
County	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Arkansas	3.60%	3.60%	12.10%	20.60%	20.60%	60.30%	60.30%
Clay	6.10%	6.10%	18.42%	30.73%	30.73%	65.36%	65.36%
Craighead	7.65%	7.65%	17.76%	27.88%	27.88%	63.94%	63.94%
Crittenden	10.23%	10.23%	20.90%	31.57%	31.57%	65.78%	65.78%
Cross	7.47%	7.47%	19.29%	31.12%	31.12%	65.56%	65.56%
Greene	6.86%	6.86%	17.07%	27.29%	27.29%	63.64%	63.64%
Independence	3.41%	3.41%	9.83%	16.25%	16.25%	58.13%	58.13%
Jackson	6.25%	6.25%	18.20%	30.14%	30.14%	65.07%	65.07%
Lawrence	4.12%	4.12%	14.62%	25.12%	25.12%	62.56%	62.56%
Lee	7.37%	7.37%	22.19%	37.02%	37.02%	68.51%	68.51%
Mississippi	12.15%	12.15%	22.06%	31.97%	31.97%	65.99%	65.99%
Monroe	4.34%	4.34%	14.69%	25.04%	25.04%	62.52%	62.52%
Phillips	4.69%	4.69%	14.80%	24.92%	24.92%	62.46%	62.46%
Poinsett	10.70%	10.70%	20.70%	30.70%	30.70%	65.35%	65.35%
Prairie	3.65%	3.65%	12.03%	20.41%	20.41%	60.21%	60.21%
Randolph	1.60%	1.60%	11.27%	20.93%	20.93%	60.47%	60.47%
St. Francis	6.82%	6.82%	21.25%	35.69%	35.69%	67.84%	67.84%
White	1.36%	1.36%	7.88%	14.39%	14.39%	57.20%	57.20%
Woodruff	7.28%	7.28%	20.47%	33.67%	33.67%	66.83%	66.83%

Table 34 : Percent demand per county for the decreasing demand pattern

	Demand Percentage						
County	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Arkansas	60.30%	60.30%	20.60%	20.60%	12.10%	3.60%	3.60%
Clay	65.36%	65.36%	30.73%	30.73%	18.42%	6.10%	6.10%
Craighead	63.94%	63.94%	27.88%	27.88%	17.76%	7.65%	7.65%
Crittenden	65.78%	65.78%	31.57%	31.57%	20.90%	10.23%	10.23%
Cross	65.56%	65.56%	31.12%	31.12%	19.29%	7.47%	7.47%
Greene	63.64%	63.64%	27.29%	27.29%	17.07%	6.86%	6.86%
Independence	58.13%	58.13%	16.25%	16.25%	9.83%	3.41%	3.41%
Jackson	65.07%	65.07%	30.14%	30.14%	18.20%	6.25%	6.25%
Lawrence	62.56%	62.56%	25.12%	25.12%	14.62%	4.12%	4.12%
Lee	68.51%	68.51%	37.02%	37.02%	22.19%	7.37%	7.37%
Mississippi	65.99%	65.99%	31.97%	31.97%	22.06%	12.15%	12.15%
Monroe	62.52%	62.52%	25.04%	25.04%	14.69%	4.34%	4.34%
Phillips	62.46%	62.46%	24.92%	24.92%	14.80%	4.69%	4.69%
Poinsett	65.35%	65.35%	30.70%	30.70%	20.70%	10.70%	10.70%
Prairie	60.21%	60.21%	20.41%	20.41%	12.03%	3.65%	3.65%
Randolph	60.47%	60.47%	20.93%	20.93%	11.27%	1.60%	1.60%
St. Francis	67.84%	67.84%	35.69%	35.69%	21.25%	6.82%	6.82%
White	57.20%	57.20%	14.39%	14.39%	7.88%	1.36%	1.36%
Woodruff	66.83%	66.83%	33.67%	33.67%	20.47%	7.28%	7.28%

Table 35: Percent demand per county for the constant demand pattern

State	Demand Percentage
Arkansas	25.87%
Clay	31.83%
Craighead	30.96%
Crittenden	33.72%
Cross	32.51%
Greene	30.38%
Independence	23.63%
Jackson	31.59%
Lawrence	28.32%
Lee	35.43%
Mississippi	34.61%
Monroe	28.36%
Phillips	28.42%
Poinsett	33.46%
Prairie	25.80%
Randolph	25.32%
St. Francis	34.56%
White	21.97%
Woodruff	33.72%